National Aeronautics and Space Administration

Prognostics Testbed

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Problem

Motivation

To facilitate research in prognostics, it is imperative to have a hardware testbed that mimics the complexities and issues encountered for a real system.

Such a system will support

- Algorithm development
- Testing and validation of prognostic tools
- Benchmarking of different approaches
- Development of metrics for prognostics
- Collection and dissemination of run-to-failure data

Goal

- Demonstrate ability to distinguish between components at different health states having similar external observables and then to predict the end of life

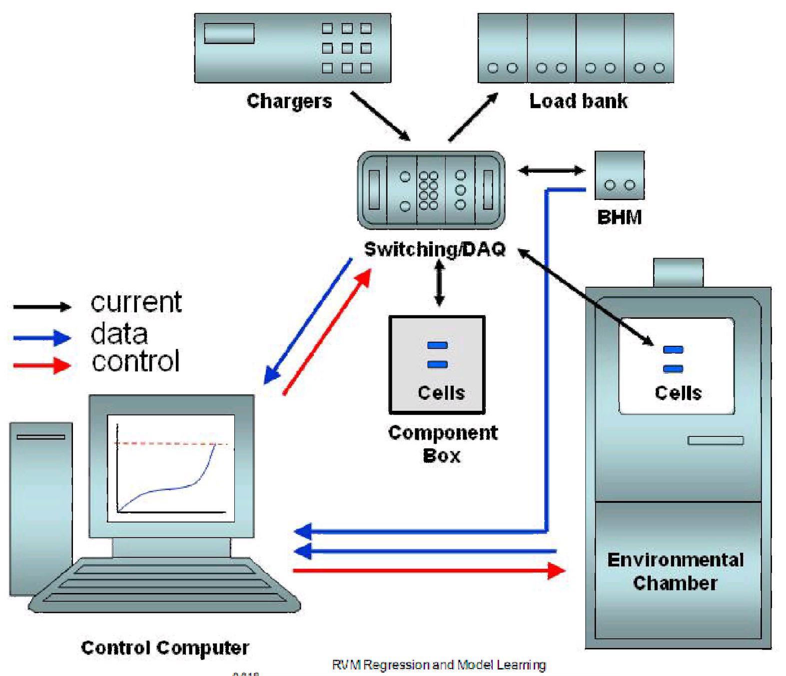
Requirements

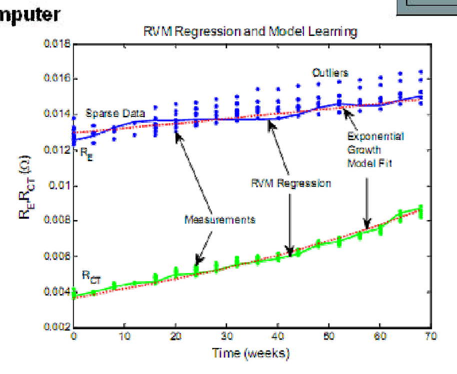
The testbed shall:

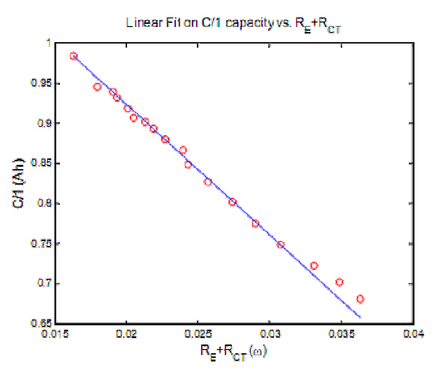
- Resemble a system that has real-world relevance
- Allow for repeated run-to-failure of components
- Perform run-to-failure in reasonable time
- Support monitoring of ground truth
- Collect data for state assessment
- Support demonstration of prognostic solutions
- Allow control of several operational and/or environmental variables
- Allow quantification of uncertainty sources
- Support repeated run-to-failure within a finite budget
- Support automated data collection during the aging

System

Testbed – Data Collection

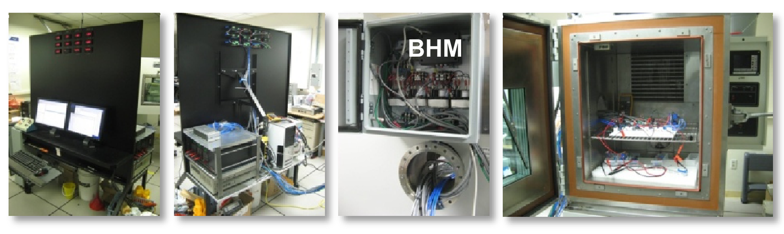


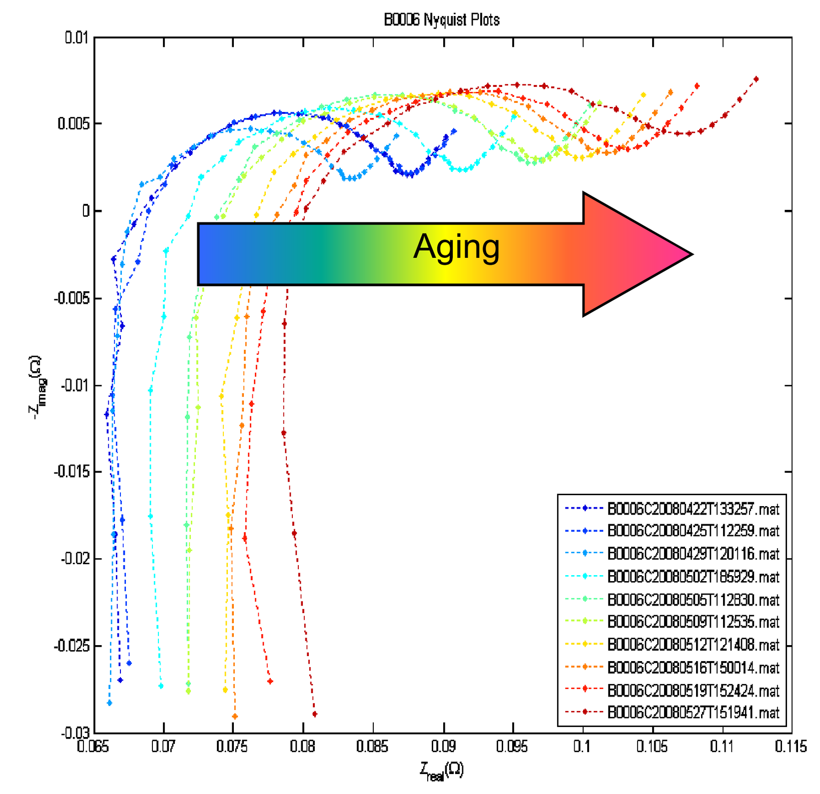




Experimental setup

- A set of Li-ion cells
  - Aging dynamics slow enough to be observable and fast enough for reasonable run-to-failure times (~1 month)
  - Low cost
  - May be aged either inside or outside an environmental chamber
- Programmable Charger and Electronic Load
- EIS equipment for battery health monitoring (BHM)
- Sensor suite – Voltage, Current, Temperature
- Custom switching circuitry
- Data acquisition system
- Computer for control and analysis





Experimental Plan

- Cells are cycled through charge and discharge under different load and environmental conditions set by the electronic load and environmental chamber respectively
- Periodically EIS measurements are taken to monitor the internal condition of the battery
- DAQ system collects externally observable parameters from the sensors
- Switching circuitry enables cells to be in the charge, discharge or EIS health monitoring state as dictated by the aging regime

Results

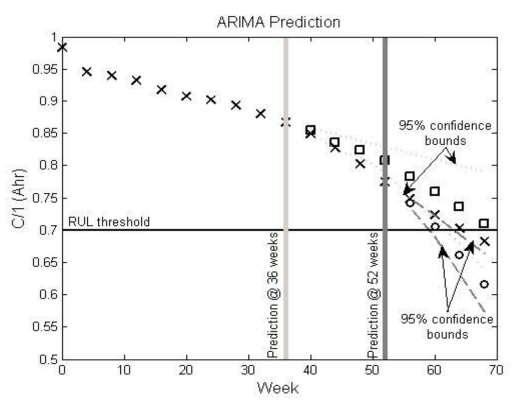
Algorithm Development

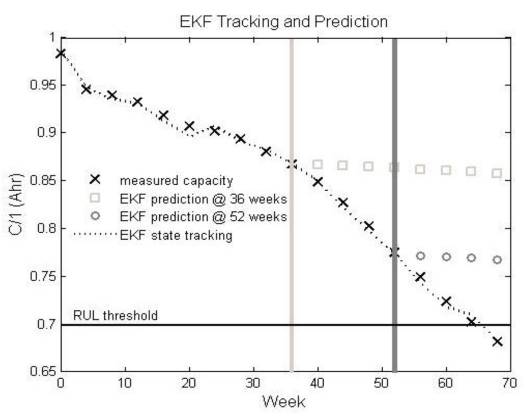
The algorithms considered so far include both model-based as well as data-driven algorithms, for example

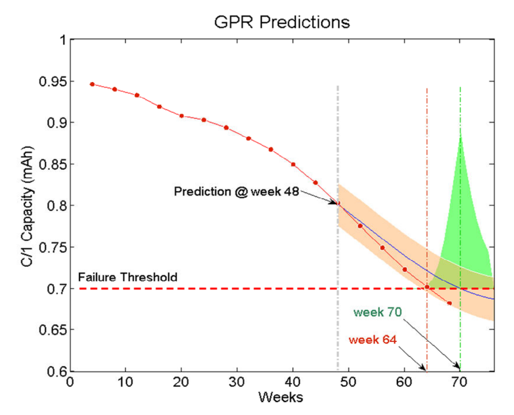
- Relevance vector machines (RVM)
- Gaussian Process Regression (GPR)
- Particle Filters (PF, RBPF)
- Neural Networks (NN)
- Random Forest Regression
- ARIMA models
- Kalman Filters

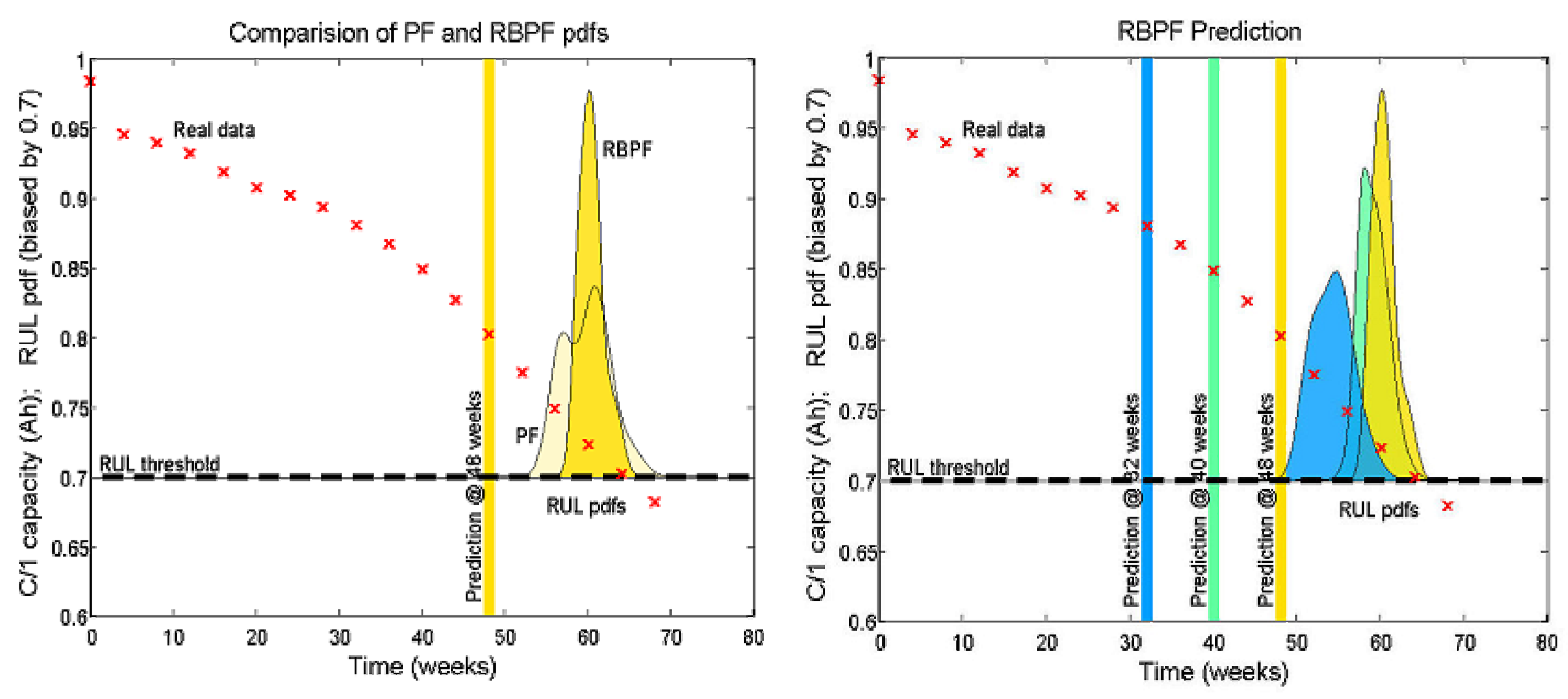
Further algorithms will be explored and results will be published to disseminate findings on advantages and disadvantages of each one.

Sample Results









Battery Prognostics

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Problem

Electric Propulsion Space Experiment (AFRL)

- Ammonia Arcjet onboard ARGOS (1999)
- Gases released from **electrolyte decomposition** resulted in a breach of the battery case, **releasing superheated gas** into the unit

(Courtesy: AFRL-PR-ED-TR-2001-0027)

Beech A200 (Reg # N258AG)

- Onboard **generators failed** to activate as starter was still engaged after ignition
- **Battery completely discharged** resulting in **total electrical failure** disabling normal landing gear extension capability
- Landing gear failed & the plane crashed

(Courtesy: NTSB, ID #SEA00LA066)

Mars Global Surveyor

- The MGS failed Nov 2006

"We think that the failure was due to a software load ... The radiator for the battery pointed at the sun, the ***temperature went up****, and* ***battery failed****..."*

John McNamee Mars Exploration Program, NASA

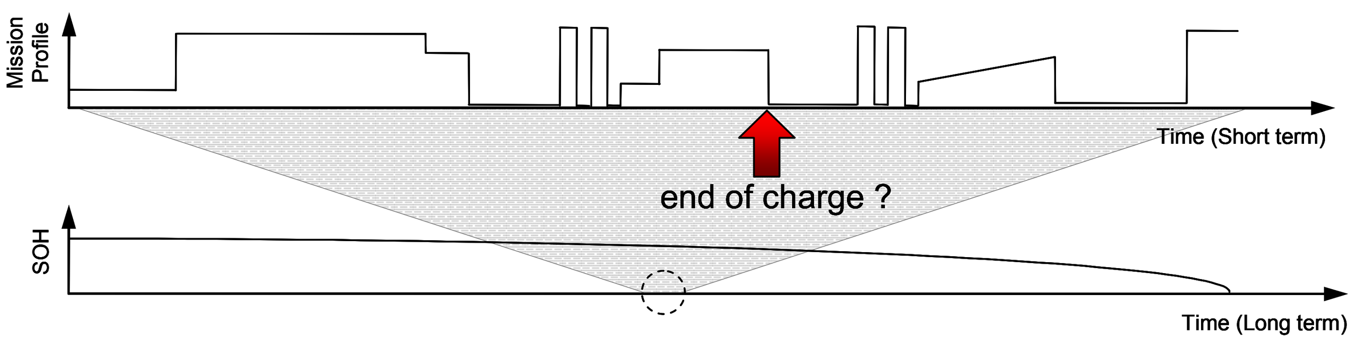
Questions to be Answered

Can the current mission be completed?

- Given the health of the battery, is there enough charge left for anticipated load profile (within allowable uncertainty bounds)?
- Dominant metrics: state of charge (SOC), state of health (SOH)

Can future missions be completed?

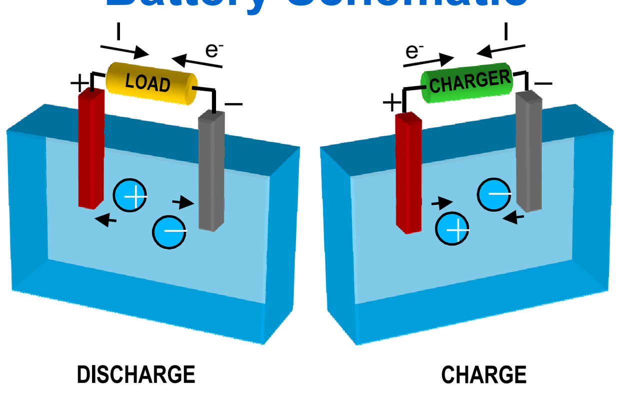
- Given the health of the battery, at what point can typical future missions not be met?
- Dominant metrics: end of life (EOL), state of health (SOH)



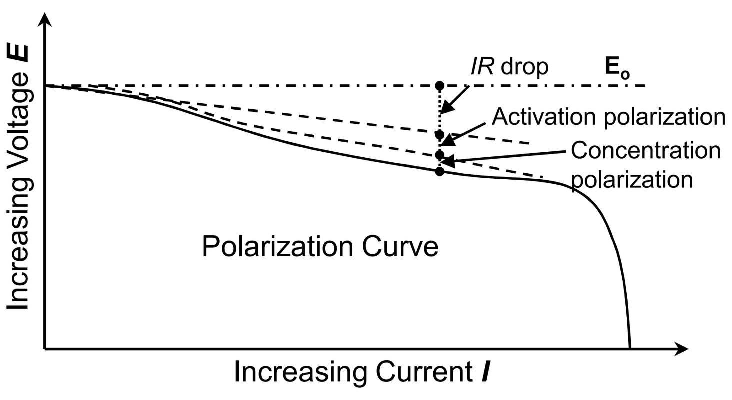
GOAL: *Develop a model that makes a prediction of* ***end-of-charge*** *and* ***end-of-life*** *based on rapid state of health (SOH) assessment*

Approach

Battery Schematic

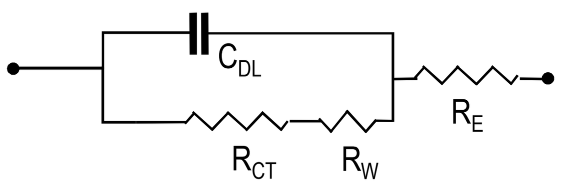


- The External Voltage (E) of a battery is less than its Open Circuit Potential (E_o) whenever it is in use.
- Losses are due to:
  - R_o: Internal Resistance (IR drop),
  - R_p: Polarization Resistance
  - R_c: Concentration Polarization
- These losses tend to increase as the current drawn from the battery increases.



Ohmic resistance (R_o) and polarization resistance (R_p) of a Li-ion battery gradually increase with aging

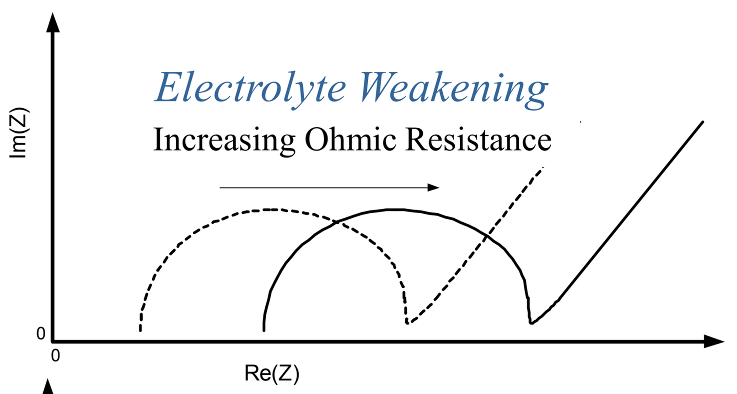
Lumped Parameter Model

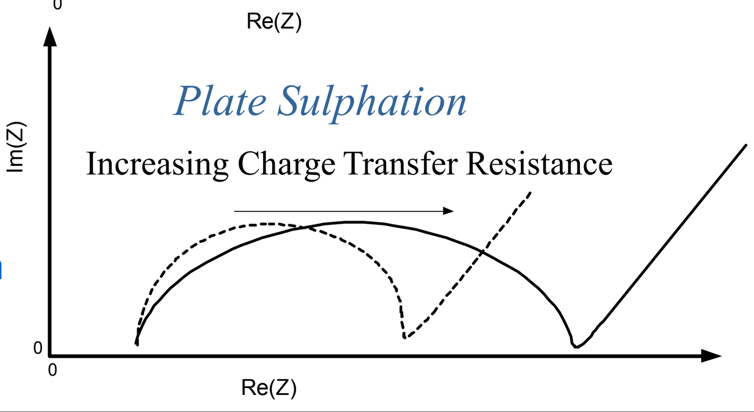


Impedance = Resistance + Reactance

Electrochemical Impedance Spectroscopy (EIS)

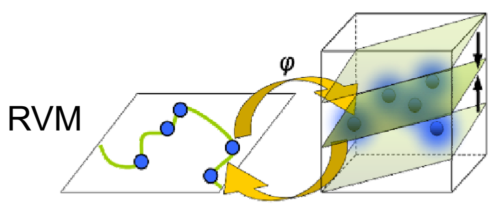
- Carry out a frequency sweep
- Plot Capacitive (1/ωC) v/s Resistive (R) component of the Reactance
- Response is different in presence of passivation and corrosion, providing a diagnostic for the health state of battery





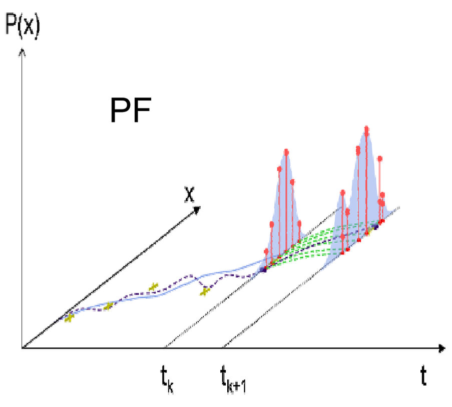
Relevance Vector Machine

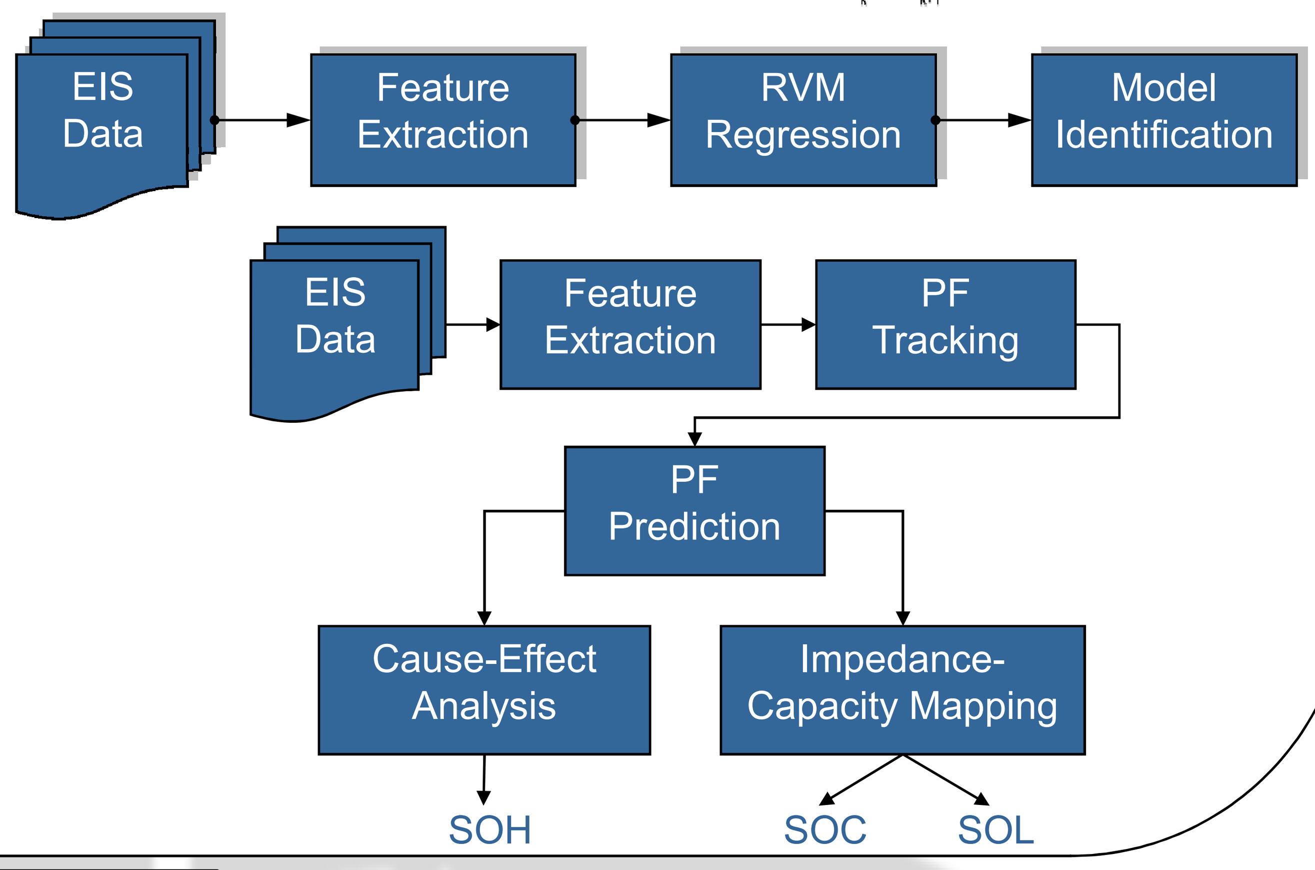
- State of the art in nonlinear probabilistic regression
- Data driven learning
- Learn degradation mode



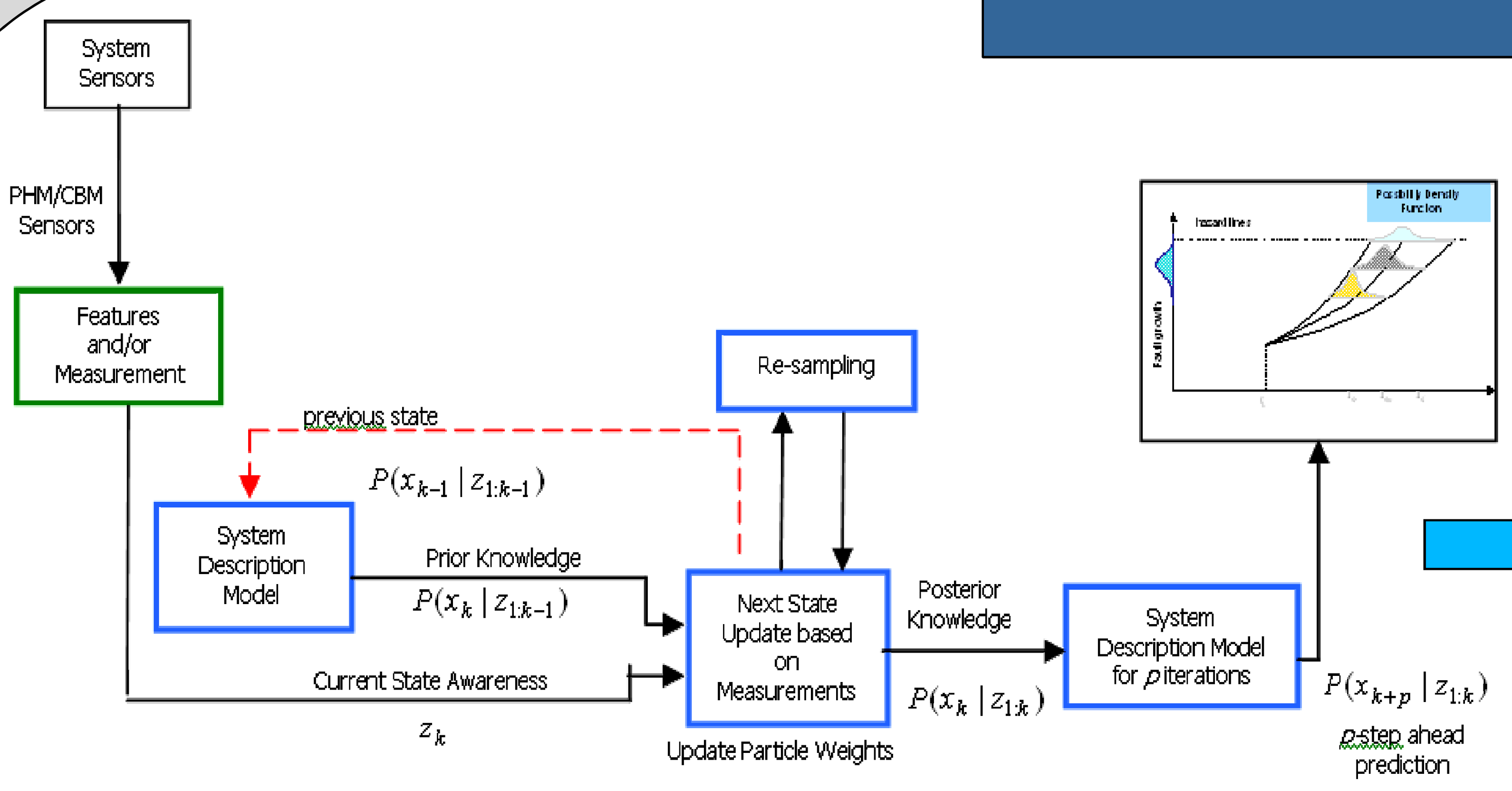
Particle Filter

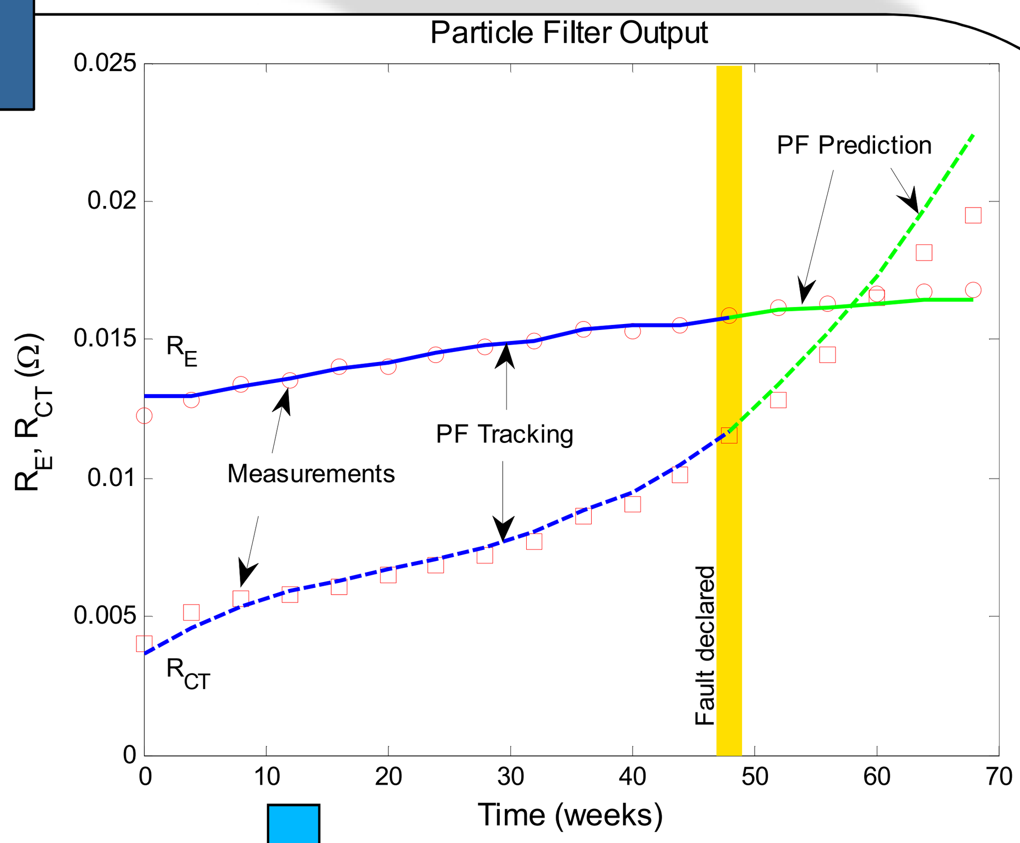
- State of the art for nonlinear non-Gaussian state estimation
- Uses model to predict and data to correct prediction
- Sequential Monte-Carlo simulations with Importance Sampling for *p*-step ahead predictions

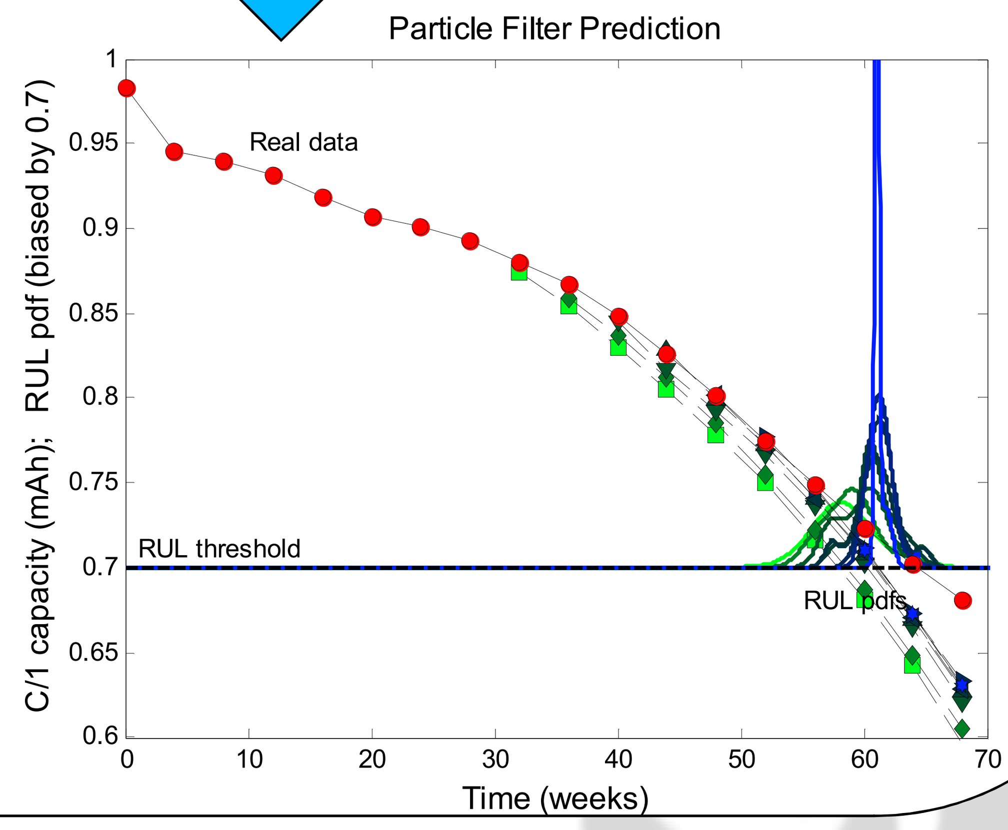


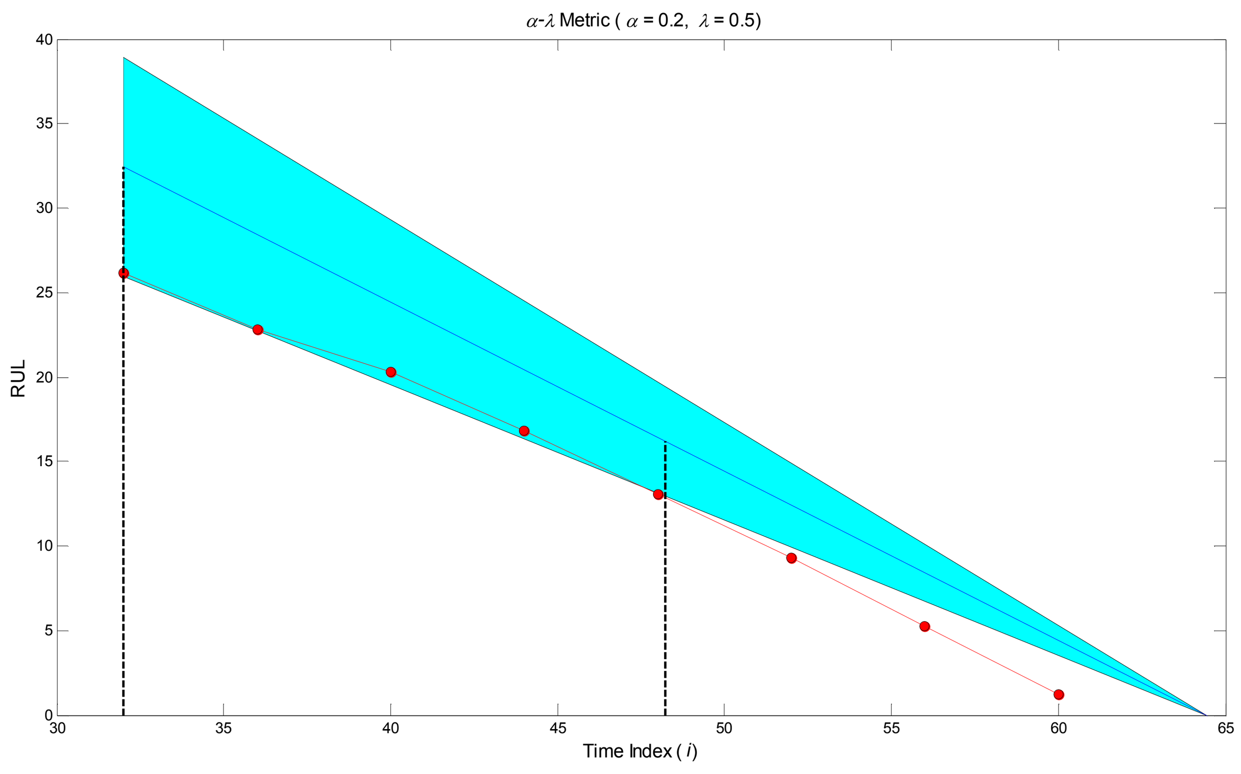


Results









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